Mapping the Future: Spatial Models of Decadal-Scale Landscape Change in Northern Australia

Brook, B. W., **D.M.J.S. Bowman and C.J.A. Bradshaw**

[1]School for Environmental Research, Charles Darwin University, E-Mail: barry.brook@cdu.edu.au

Keywords: *Aerial photography, Bootstrapped coefficients, Historical ecology, Generalized linear modelling, Geographic Information Systems, Landscape ecology, Vegetation dynamics.*

EXTENDED ABSTRACT

Repeated sequences of digitised and geo-referenced historical aerial photography provide a powerful means of understanding landscape change over time scales beyond conventional ecological monitoring, especially in remote areas. We use this method to develop spatially explicit models of vegetation change at five sites in the Australian monsoon tropics, and assess the goodness-of-fit of the model to observed change. Models were derived by (i) converting the landscape into cells using a grid-overlay method and classifying vegetation as either closed forest (CF) or savanna (SV); (ii) examining repeat sequences of aerial photographs (taken in 1947, 1972 and 1997) to determine the temporal sequence of vegetation change in each cell (i.e., stasis versus change to different vegetation class); (iii) using thematic layers to derive cell-based measures of elevation, slope angle and drainage distance; (iv) counting the number of like-habitat points in the area surrounding each cell, with the fractal dimension of this area also calculated; and (v) using a bootstrapped generalised linear modelling approach (which controls for potential spatial autocorrelation) to derive a cell-based probability map of change based on the landscape features from (iii) and (iv) fitted to (ii) (an example is given in Figure 1).

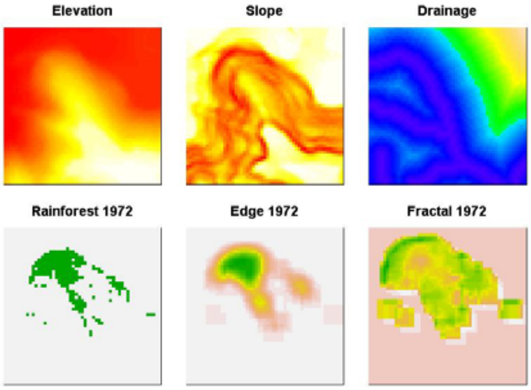


Figure 1. Landscape habitat attributes at the McDermott's Spring site in the Gulf of Carpentaria region of the Northern Territory, Australia, showing topographic elevation, slope gradient and distance from drainage lines (top row), and a map of closed forest distribution in 1972 and the calculated proportion of like-habitat verus non-like (edge) and fractal dimension of closed forest, based on point-wise assessment of the two surrounding layers of 20 x 20 m grid cells.

Overall, the closed forest expanded by an average of 42 % total coverage over the fifty-year period, although the rate of change varied across sites. The dynamics of the closed forest-savanna system were predicted with reasonable reliability based on a comparison of observed and predicted CF coverage and the ratio of cells correctly versus incorrectly predicted to change from CF to SV, or vice versa. Mean per cent discrepancy between observed and predicted coverage of CF among sites was only 1.03 % (range: 0 to 2.3 %), and the overall spatial agreement between observed and predicted maps was 88.9 % (range: 78.9 to 94.1 %). Model fit based on the average of two 25-year couplets (1947-1972 and 1972-1997) was consistently superior to those based on a single 50-year couplet (1947-1997). Single-couplet fits had a mean deviance from the observed CF coverage of 6.2 % (range: 0.4 to 23.2 %), compared to only 0.9 % (range: 0.2 to 2.1 %) for the average of two couplets. Spatially explicit fits were also superior for two vs. one time couplet (87.1 vs. 85.0 %, respectively).

CF expansion occurred most frequently in fire-protected sites along forest edges and regression in the more fire-prone areas. Possible drivers for this expansion may include changed fire regimes associated with the cessation of traditional Aboriginal fire management or the 'fertilizer' effect caused by the continued increase in global atmospheric CO_2 over the course of the 20th century. This effect may be changing the competitive balance between C_3 trees of the CF the largely C_4 tropical grasses of the SV. Our results also demonstrate quantitatively the benefit of the additional information contained in repeat sequences of imagery over 'snapshots' taken only at the beginning and end of an observation period.

1. INTRODUCTION

The landscapes of northern Australia are characterised by vast stretches of tropical wooded savannas, with a scattering of small patches of closed forest (usually wet-dry rainforest) that persist in fire-protected refuges with sources of permanent water (such as sandstone gorges; Bowman 1998). Recent research has provided evidence for a strong link between global vegetation patterns and fire activity (Bond *et al.* 2005), and there is considerable interest in the pattern and rate of biogeographic change of vegetation types associated with anthropogenically mediated global environmental change (Bowman 2000, Bond *et al.* 2003) such as global warming and enrichment of atmospheric CO_2 linked to ongoing industrial pollution (Keeling and Whorf 2004). Recent research has indicated a dramatic expansion of the closed-canopy forest systems of northern Australia despite an apparent increase in the frequency, intensity and coverage of landscape fire (Bowman *et al.* 2001, Russell-Smith *et al.* 2004). A natural question that arises from these findings is: are the observed changes in vegetation distribution in the tropical savannas explicable on the basis of localised landscape-scale features or are any such signals swamped by regional and global environmental controls, making localised spatial predictions impossible beyond a general forecast of rate of change?

The historical analysis and spatial modelling of decadal-scale vegetation change is a rapidly developing field (Guisan and Zimmermann 2000). This modelling commonly employs digitised temporal sequences of aerial photography to discern long-term landscape-scale patterns in vegetation structure (Augustin *et al.* 2001). For example, Bowman *et al.* (2001) used this approach to document an expansion of closed forest in the Northern Territory between 1941 and 1994 over a 30 km^2 area. Implicit in this analysis was that a single couplet of images spanning 50 years was able to meaningfully capture the vegetation dynamics. This underscores a serious limitation of aerial photography – the infrequent acquisition of data in the temporal stream makes predictive modelling of dynamic systems difficult. While it is obvious that the inclusion of additional time sequences adds information on trajectories of vegetation change, its integration poses some methodological challenges. The purpose of this paper is to develop the most-robust models describing vegetation change and to quantify the contribution of additional temporal information to model goodness-of-fit.

2. STUDY LOCATION

We assessed and modelled five sites within a radius of 37 km (the closest of the four sites are 10 km apart) on the Wollogorang pastoral property in the southwest of the Gulf of Carpentaria, Northern Territory, Australia (17º 11' S,137º 46' E; Figure 2). The region is in the southern arid limit of the monsoon tropics, with an average annual rainfall of 850 mm (falling largely between December and March), and an average daily temperature of 33 ºC (Northern Territory Bureau of Meteorology: http://www.bom.gov.au/weather/nt/).

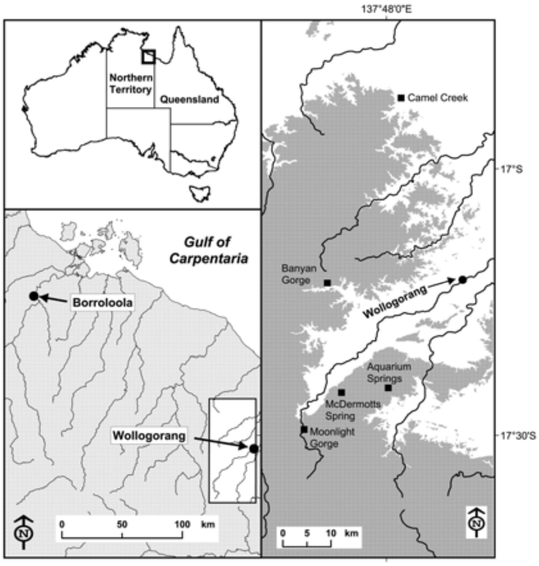


Figure 2. Location of the study area at continental, regional and local geographic scales. At the local scale, areas greater than 400 m elevation are shaded and major drainage lines marked. Also indicated are the positions of the five sandstone gorge sites.

3. AERIAL PHOTOGRAPHIC ANALYSIS

Historical aerial photography was acquired for three time-slices (1947 [1:50000 black and white], 1972 [1:25000, colour] and 1997 [1:25000, colour]) for four sites (Aquarium Springs = AQ, Banyan Gorge = BA, McDermott Springs = MD and Moonlight Gorge = MO), and two time slices (1952 [black and white] and 1995 [colour]) for a fifth, slightly more northerly and isolated site (Camel Creek [CC]). Figure 3 provides an example photographic sequence for the MD site.

All sites contain gorge-protected closed canopy forest embedded in a wooded savanna matrix. The imagery was scanned to a pixel resolution of 1 m^2 and ortho-rectified using ERDAS Imagine v8.4 to 1:50000 topographic map sheets. Using ArcView v3.2, a lattice of points spaced 20 x 20 m was then overlain on each scanned and rectified aerial photograph, and assigned to either wooded savanna (SV: tree crowns spaced > 20 m apart) or closed forest (CF: ≤ 20 m apart) habitat types.

Figure 3. Repeat sequence of geo-referenced aerial photography at the McDermott's Spring site in 1947, 1972 and 1997.

Ground-truthing for our binary classification of canopy cover was made at 63 point locations were made independently using a densiometer at BA in the wet season (February) 2002, and showed a clear difference in canopy cover between those sites mapped using the 1997 imagery as CF (mean ± standard error = 84.4 % ± 1.9, $n = 36$) compared to SV (28.3 % ± 3.7, $n = 27$). An example of the lattice grid maps are provided in Figure 4.

Arcview was used to derive from the thematic layers the following attributes for each lattice point: distance (m) to drainage line (DR), topographic elevation (m) above sea level (EL), and slope (average gradient between a given point and all surrounding points, SL). The lattice was then converted to a 20 m raster grid of dots and exported to the *R*-package v2.1.1 (http://r-project.org/) for all further analyses. The vegetation mapping from the aerial photography was used to count the number of like-habitat points (LH) in the surrounding area (A) at each of 1 to 4 encircling layers of cells, with the fractal dimension (FR) also calculated as $2\log_e(0.25P)/\log_e(A)$, where P = total perimeter (Hargis et al. 1998). An example of the spatial configuration of the physical and vegetation variables is provided in Figure 1. The temporal change in the vegetation type of each point between both 1947-1972 and 1972-1997 was then assessed, with the possible transitions being no change (CF-CF or SV-SV), closed-forest regression (CF-SV) or closed-forest expansion (SV-CF), a method akin to that used by Augustin *et al*. (2001).

4. MODELLING

4.1. Statistical framework: generalised linear models (GLM) of landscape change

Using the lattice points of vegetation and thematic data extracted, we developed two statistical probability relationships to underpin our predictive models: (i) a closed-forest change model, where the dependent variable of a binomial GLM (logit-link) was whether a CF point changed to SV in either the periods 1947-1972 or 1972-1997 (coded as a 1), or remained CF throughout (coded as a 0). The independent predictor variables were the physical attributes of the landscape (EL, SL, and DR) and the measures of the amount and patchiness of proximate vegetation of the same type (LH and FR); (ii) a savanna change model which had the same structure as (i) except that the dependent variable was the change (or not) from SV points to CF. Spatial autocorrelation that can result in statistically non-independent data was accounted for by sub-sampling (with replacement) from the full suite of lattice points and repeatedly refitting the GLMs (1000 bootstrap iterations per model).

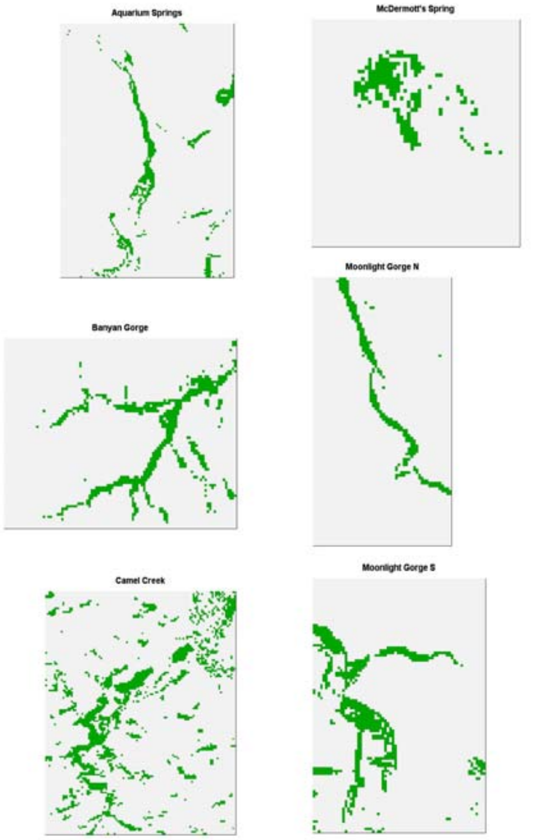


Figure 4. Digitised maps of closed-forest coverage at the five study sites in 1947 (1952 for Camel Creek), including a split of the large Moonlight Gorge into northerly and southerly sections.

4.2. Probability-based spatial model fits

The two GLMs described in 4.1 were used to develop a map of change probability for each site via a back-transformation of the logit fits for CF and SV at each lattice point. We then searched iteratively for the optimal probability threshold above which a change in vegetation state was predicted to occur, and the optimum buffer size for calculating LH and FR. This optimum was decided by evaluating simultaneously three measures of goodness-of-fit across the site map: (i) the difference between the observed and model-predicted per cent coverage of CF, the percentage of lattice points in which the predicted vegetation type agreed with the observed type, and the ratio of cells correctly versus incorrectly predicted to change from CF to SV, or vice versa (e.g. a ratio of 1.0 = 50% right, 50% wrong; 2.0 = 67% right, 33% wrong; 0.5 = 33% right, 67% wrong). This was repeated for each site (except CC) and each time couplet (1947-1972 and 1972-1997).

4.3. Slicing the past: Is more better?

We examined whether the inclusion of intermediary vegetation data between time slices influenced the predictive capacity of the models. We constructed GLMs to describe the transition of CF to SV and SV to CF from 1947-1997 (i.e., excluding the 1972 data) to reconstruct a predicted map of the 1997 distribution of forest types for the sites AS, BA, MD, MN and MS. All probability-based spatial fits were derived in an identical manner to those described previously. These model fits were compared to a predicted 1997 map constructed by taking the average of the GLM coefficients derived from the 1947-1972 and the 1972-1997 transitions. The means of these coefficients for each predictor were used to construct an average transition probability for each lattice point, and then these transition probabilities were squared to provide a full-interval (i.e., 50 years) fit for 1997. We compared these two fits (one vs. two time couplets) to the observed 1997 distribution maps by examining the percentage coverage of CF and the percentage of lattice points that agreed with the observed map.

5. RESULTS

5.1. Closed forest expansion

When taken over all five sites over the 50-year study there was a substantial increase (mean weighted by area of site = 42 %; see Tables 1 and 2 for individual sites) in the coverage of closed forest in the landscape, although this change was variable across sites (e.g., the areas of closed forest at the MD site more than doubled whereas the increase at Moonlight Gorge site [MN and MS combined] was only 11 %). Examination of vegetation change maps (Figures 5 and 6, left columns) reinforces the notion that the process of closed forest expansion is neither uniform in space or time at any of the sites. Although the basic spatial configuration of SV and CF does not change greatly over time, the CF expansion clearly occurs most readily through growth out from existing core areas (with some establishment of isolated nuclei), whereas regression of closed forest to savanna tends to be restricted to edges of closed forest in particular landscape settings.

Table 1. Observed vs. predicted change between 1947-1972. Shown are the observed % changes in CF area (negative values indicate an overall contraction of forest), observed and model-predicted % coverage of CF in 1972, % of lattice grid cells in which the predicted vegetation type agreed with reality, ratio of cells correctly versus incorrectly predicted to change from CF to SV, or vice versa, the optimal buffer size for calculating LH and FR, and the optimal probability threshold

(as predicted for each cell) above which a change in vegetation state would be predicted to occur.

	Observed		Predicted		Right : Wrong			
Site	O(%ΔCF)	O(%CF)	P(%CF)	% Agree	CF-SV	SV-CF	Buf	Thr
AS	27.1	5.9	6.1	93.5	0.96	0.52	2	0.22
BA	26.3	10.8	12.7	88.9	0.84	0.49	1	0.29
MD	21.3	7.0	7.1	94.1	2.29	0.88	1	0.32
MN	129.1	10.7	11.4	93.4	1.56	2.00	1	0.27
MS	-21.1	8.0	6.3	89.4	1.89	0.64	1	0.23

5.2. Agreement between model fit and data

There is a clear visual (Figures 5 and 6) and quantitative (Tables 1 and 2) agreement between the spatial distribution of prime closed-forest habitat identified by the model and the observed expansion of the closed forest between 1952 and 1995. This suggests that the model provides a reasonable description of reality. The probability models for predicting vegetation change seem to fail most frequently along the borders of CF regressions, possibly because the temporal processes involved in SV expansion are continuous and cumulative, whereas the destruction of CF would be more episodic (associated with disturbance events) and the coarse temporal resolution of the sampling may capture inadequately all such regressive events. Some error is also likely to result from imperfections in the digitizing and georeferencing process.

Table 2. Observed vs. predicted change between 1972-1997. Attributes as per Table 1.

	Observed		Predicted		Right : Wrong			
Site	O(%ΔCF)	O(%CF)	P(%CF)	% Agree	CF-SV	SV-CF	Buf	Thr
AS	16.4	6.9	6.6	91.1	1.09	0.49	1	0.27
BA	36.4	14.7	17.0	78.9	1.31	0.59	1	0.22
CC	10.6	14.5	14.5	83.7	1.47	1.13	1	0.27
MD	107.8	16.7	18.6	88.1	0.24	0.79	3	0.33
MN	4.12	11.1	11.1	84.8	1.34	0.75	1	0.08
MS	5.5	8.6	6.4	92.4	2.35	0.45	3	0.19

In all sites except MN there was a better agreement between the per cent CF coverage in the observed data to the predicted map based on two time couplets (Table 3). Therefore, the inclusion of an intermediary time slice generally improves predictive capacity. The % agreement between the observed and predicted maps were generally similar for the one- and two-slice model fits; however, this index was weighted heavily towards the dominate SV lattice points.

6. DISCUSSION

6.1. Modelling vegetation change

Repeat sequences of historical aerial photography enabled the description of vegetation change over long time periods with precise time control and a high degree of spatial resolution across entire landscapes (Bowman *et al.* 2001, Russell-Smith *et al.* 2004).

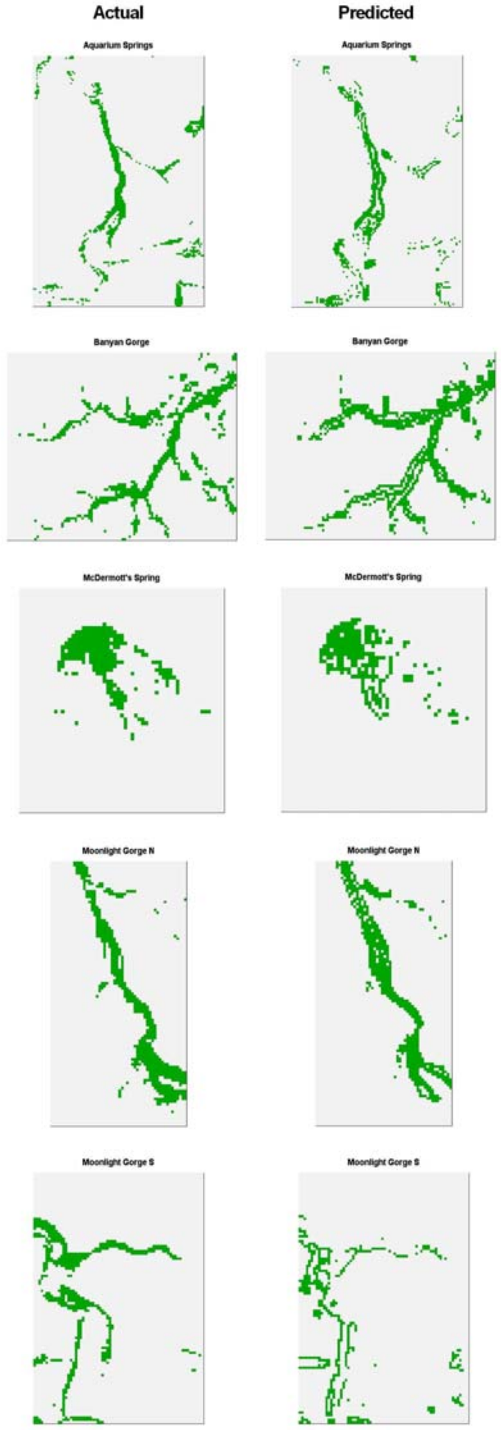
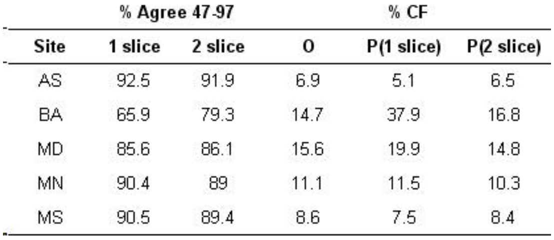


Figure 5. Agreement between the observed distribution of CF in 1972 and that predicted by the vegetation-specific GLMs (estimated using bootstrapped median coefficients) based on the distribution of CF in 1947.

Nevertheless, it is prone to irregular data acquisition and technical issues of standardisation that affect the quality of the data (e.g. differing film/camera types or photographic scales). The approach developed here maximises the use of the information contained in this environmental archive and differs from that of Augustin *et al.* (2001), who calculated transition probabilities that were de-coupled from environmental gradients. It is self-evident that such geospatial models that fail to consider the importance of physical and environmental attributes of landscape that mediate vegetation dynamics will have reduced predictive capacity. For instance, the probability components in Markov-chain cellular automata models (Balzter *et al.* 1998) should vary in response to habitat suitability. We have demonstrated that local effects strongly constrain vegetation change at the landscape scale, despite a regional tendency for closed forest expansion.

Not only have we demonstrated geophysical constraints to vegetation change, the subsequent trajectories are also sensitive to the spatial arrangement of vegetation types at each time step (characterised by the fractal dimension). This creates difficulties for parameterisation of growth models because there is a mismatch between the biological processes (continuous) and the observed ‘snapshots’ of change (discrete). For instance, the growth of woody vegetation (conversion of SV to CF) occurs continuously at the annual time-scale due to assimilation of carbon and dispersal of propagules, with disturbance leading to regression operates more stochastically (e.g., destruction of many trees by wildfires). The fact that there was such a substantial improvement in model fit using two rather than one time couplet of time couplets provides hope that a greater number of images will permit a closer approximation of the behaviour of the biological system.

Table 3. Relative goodness of fit of one versus two time couplets in predicting vegetation change over the period 1947-1997 at all sites except CC.



	% Agree 47-97			% CF	
Site	1 slice	2 slice	O	P(1 slice)	P(2 slice)
AS	92.5	91.9	6.9	5.1	6.5
BA	65.9	79.3	14.7	37.9	16.8
MD	85.6	86.1	15.6	19.9	14.8
MN	90.4	89	11.1	11.5	10.3
MS	90.5	89.4	8.6	7.5	8.4

6.2. Environmental determinants of change

The landscape-wide expansion of CF observed in the semi-arid Gulf of Carpentaria region matches

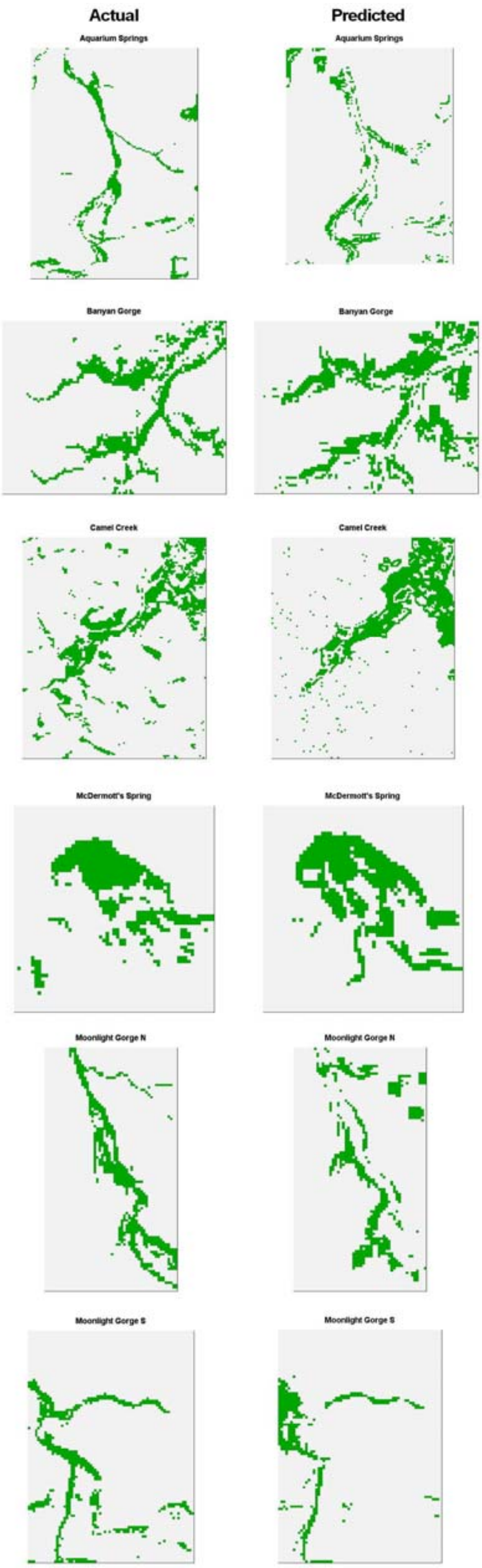


Figure 6. Agreement between the observed distribution of CF in 1997 (1995 for Camel Creek) and that predicted by the vegetation-specific GLMs (estimated using bootstrapped median coefficients) based on the distribution of CF in 1972 (1952 for Camel Creek).

the pattern observed at the other mesic extreme of the closed-forest distribution in the Northern Territory (e.g., Bowman *et al.* 2001). Although our modelling is not mechanistic and cannot be used to identify the specific contribution of various drivers of landscape change, it can be used to identify plausible controls. For instance, we infer that landscape fire has played a role in constraining the expansion of closed forests because SV-CF conversion occurred preferentially on sites that had topographic features conducive to fire protection (e.g., steep slopes or proximity to drainage lines; Bowman 2000). For example, at BA the forest expanded from a core area mainly along a gorge floor, MD expanded into a rocky amphitheatre and at CC, a sheltered drainage fan was converted into closed forest. Furthermore, it is plausible that the ultimate driver of this expansion of woody vegetation is global increases in CO_2 (Keeling and Whorf 2004) which favour C_3 woody plants over C_4 tropical grasses (Bond *et al.* 2003).

7. CONCLUSIONS

The closed-forest patches that are embedded within the vast tropical savanna matrix of the northern Australian biome provide unique and irreplaceable habitats to a broad array of endemic flora and fauna (Bowman 2000). The present work illustrates the utility of historical aerial photography in identifying the landscape factors associated with vegetation change in these systems over many decades. Specifically, we have developed robust correlative models that show the relative contribution of local site factors in controlling the rate and spatial configuration of forest expansion. Our goodness-of-fit validation of these probability models of change is an important precursor to the development of dynamic, spatially explicit predictive models, such as cellular automata. However, an important component of developing such predictive models is validation against independent data sets (e.g., van Groenendael *et al.* 1996), such as recent aerial photography not used in model construction or targeted ground surveys. A final step is to move from descriptions of processes at the local patch scale to models that are sufficiently robust to be applied reliably to the variety of landscape settings to understand the consequences of global environmental change and different land management practices.

8. ACKNOWLEDGMENTS

We thank D. McIntyre and P. McMahon for their assistance in conducting the digital vegetation mapping and retrieval of GIS layers. This work was supported by funding from the Australian Research Council's Discovery Grants scheme.

9. REFERENCES

Augustin, N.H., R.P. Cummins, and D.D. French (2001), Exploring spatial vegetation dynamics using logistic regression and a multinomial logit model, *Journal of Applied Ecology*, 38, 991-1006.

Balzter, H., P.W. Braun, and W. Kohler (1998), Cellular automata models for vegetation dynamics, *Ecological Modelling*, 107, 113-125.

Bond, W.J., G.F. Midgley, and F.I. Woodward (2003), The importance of low atmospheric CO_2 and fire in promoting the spread of grasslands and savannas, *Global Change Biology*, 9, 973-982.

Bond, W.J., F.I. Woodward, and G.F. Midgley (2005), The global distribution of ecosystems in a world without fire, *New Phytologist*, 165, 525-538.

Bowman, D.M.J.S. (1998), Tansley review No. 101: the impact of Aboriginal landscape burning on the Australian biota, *New Phytologist*, 140, 385-410.

Bowman, D.M.J.S. (2000), *Australian rainforests: islands of green in the land of fire*, Cambridge University Press, 345 pp., Cambridge, UK.

Bowman, D.M.J.S., A. Walsh, and D.J. Milne (2001), Forest expansion and grassland contraction within a *Eucalyptus* savanna matrix between 1941 and 1994 at Litchfield National Park in the Australian monsoon tropics, *Global Ecology and Biogeography*, 10, 535-548.

Guisan, A., and N.E. Zimmermann (2000), Predictive habitat distribution models in ecology, *Ecological Modelling*, 135, 147-186.

Keeling, C.D., and T.P. Whorf (2004), Atmospheric CO_2 records from sites in the SIO air sampling network. *Trends: A Compendium of Data on Global Change*. Carbon Dioxide Information Analysis Center, U.S. Department of Energy, Oak Ridge, TN, USA.

Russell-Smith, J., P.J. Stanton, A.C. Edwards, and P.J. Whitehead (2004), Rain forest invasion of eucalypt-dominated woodland savanna, Iron Range, north-eastern Australia: II. Rates of landscape change, *Journal of Biogeography*, 31, 1305-1316.

van Groenendael, J.M., R.G. Roepers, I. Woltjer, and H.R. Zweers (1996), Vegetation succession in lakes of west Connemara, Ireland: Comparing predicted and actual changes, *Journal of Vegetation Science*, 7, 211-218.